

# Review of human–robot coordination control for rehabilitation based on motor function evaluation

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**ABSTRACT** As a wearable and intelligent system, a lower limb exoskeleton rehabilitation robot can provide auxiliary rehabilitation training for patients with lower limb walking impairment/loss and address the existing problem of insufficient medical resources. One of the main elements of such a human–robot coupling system is a control system to ensure human–robot coordination. This review aims to summarise the development of human–robot coordination control and the associated research achievements and provide insight into the research challenges in promoting innovative design in such control systems. The patients’ functional disorders and clinical rehabilitation needs regarding lower limbs are analysed in detail, forming the basis for the human–robot coordination of lower limb rehabilitation robots. Then, human–robot coordination is discussed in terms of three aspects: modelling, perception and control. Based on the reviewed research, the demand for robotic rehabilitation, modelling for human–robot coupling systems with new structures and assessment methods with different etiologies based on multi-mode sensors are discussed in detail, suggesting development directions of human–robot coordination and providing a reference for relevant research.

**KEYWORDS** human–robot coupling, lower limb rehabilitation, exoskeleton robot, motor assessment, dynamical model, perception

## 1 Introduction

As a wearable robot, a lower limb rehabilitation exoskeleton can provide limb support to restore human locomotion [1] and address the current shortage of medical resources. Therefore, research on this topic has gradually gained importance [2]. In the 21st century, with rapid developments in wearable exoskeleton robots for power and rehabilitation, commercial applications have begun [3]. Several theories and techniques have been formulated for lower limb rehabilitation exoskeleton robots for various types of patients [4–10].

The typical feature of a lower limb exoskeleton rehabilitation robot is that it is worn by a patient; thus, human–robot coordination control is extremely important. To this end, scholars have proposed human-in-loop systems [11,12] that aim to solve the tri-co (coexisting–cooperative–cognitive) problem [13]. Reviews on robot-assisted lower limb rehabilitation have also been

published. A review by Meng et al. [14] focused on the progress of mechanisms, training modes and control strategies for lower limb rehabilitation robots. Lower limb orthoses and exoskeleton devices are broadly reviewed according to joint types, actuation modes and control strategies [15]. Shi et al. [2] reviewed and critically evaluated the research progress in human gait analysis and systematically summarised developments in the mechanical design and control of lower limb rehabilitation exoskeleton robots. The advantages and disadvantages of the theory and technology used in prototypes and products have also been compared and summarised [16]. These reviews focused on the design and control of the systems; however, they did not provide much detail on human–robot coordinate control. A systematic overview by Yan et al. [17] outlined the assistive strategies utilised by active locomotion–augmentation orthoses and exoskeletons. Control strategies have been reviewed and classified to determine how these devices interact with users [18]. These reviews have mainly been carried out from an engineering perspective

without an in-depth analysis of the clinical rehabilitation needs of lower limbs or patient movement disorders, without considering the relationship with clinical rehabilitation in the analysis of modelling, perception and control nor the effect of the different etiologies of lower limb motor dysfunction on the robotic rehabilitation. In addition, these reviews do not provide much detail regarding the modelling of the human–robot coupling system, which is an important component of human–robot coordination.

Different fields such as robotics, biomechanics and human motor control must converge for the development of lower limb rehabilitation exoskeleton robots [19]. Therefore, patients' functional disorders and clinical rehabilitation needs of the lower limb must be analysed, forming the basis for human–robot coordinate control of lower limb rehabilitation robots. When coupling the robot and the human body, the system must be analysed and modelled, also forming the basis of human–robot coordinated control. Accordingly, a perception system is designed to process multi-fusion information and provide the necessary feedback for the control of the robot. In the cases of demand, model and feedback, a control strategy is designed to achieve human–robot coordinated control. Therefore, to provide a reference for related research, this paper reviews human–robot coordination control of lower-limb rehabilitation robots from four aspects, including demand analysis, system modelling, sensing and control strategies. Based on the reviewed research, the demand for robotic rehabilitation, modelling for human–robot coupling systems with new structures and assessment methods with different etiologies based on multi-mode sensors mechanism of rehabilitation and the needs of patients in rehabilitation are discussed in detail, suggesting development directions of human–robot coordination and providing a reference for relevant research.

## 2 Motor function assessment for rehabilitation

Motor function assessments are essential during rehabilitation, which can help us understand the functional state

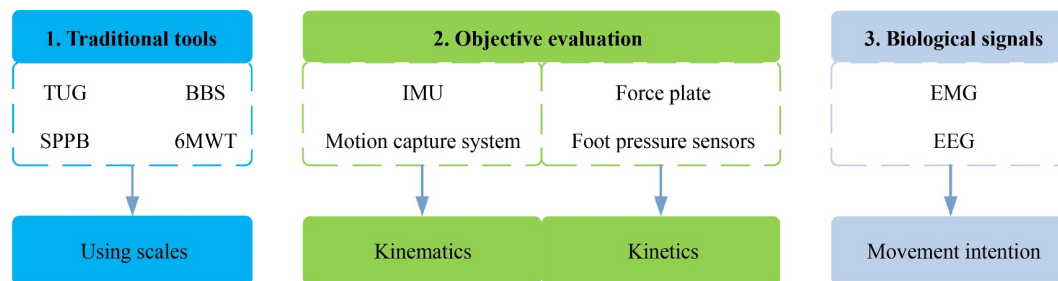
of patients. Many different methods and tools are used to evaluate motor functions, including traditional tools and objective-evaluation-based and biological-signal-based methods (Fig. 1).

### 2.1 Traditional tools

Traditional tools (such as scales) can evaluate many motor functions, including walking ability, balance, endurance, strength, and gait. The roles of different tools overlap. For example, the timed up and go (TUG) test is widely used to evaluate balance and walking ability [20,21], while the Berg balance scale and the short physical performance battery are also used for balance assessment [22,23]. In another study, TUG was used to predict the risk of falls in the elderly [24]. The 6-min walk test (6MWT) is a submaximal exercise test that measures the distance in meter (m) traversed over 6 min and provides cardiopulmonary and musculoskeletal functional capacity information. Therefore, different tools have been used for the same motor function in different studies. Conversely, the same tools may be used for different motor functions. The interpretation of each tool may vary from one study to another. Traditional tools can provide a global description of the functional state but cannot quantify real-time movement information in motor function assessment.

### 2.2 Objective-evaluation-based method

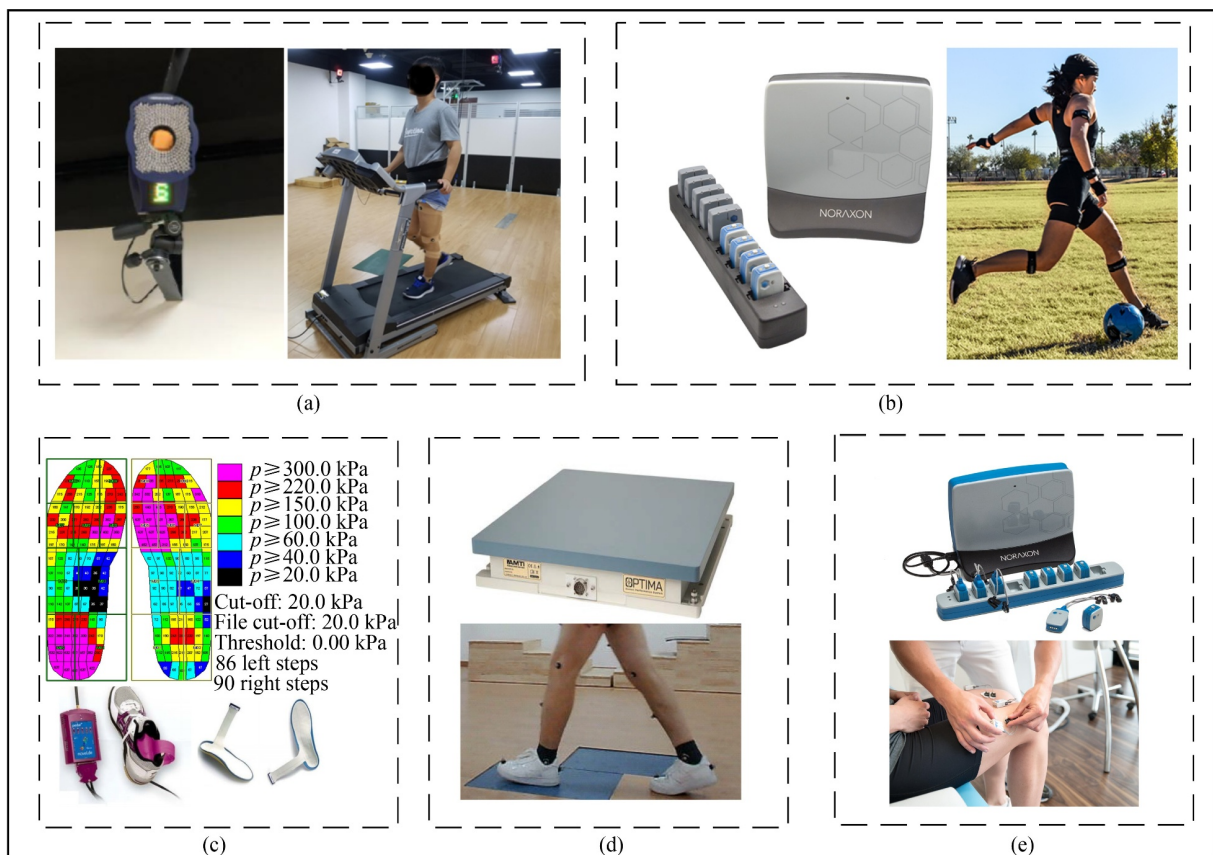
The progress of new technologies has given rise to devices including inertial measurement units (IMUs), motion capture systems, force plates, and foot pressure sensors. These devices allow an objective evaluation of human movements, providing us with the movement information of patients. This information provides a better understanding of how humans control their movements. Motor control strategies are essential for understanding the patient's motor dysfunction and finding new rehabilitation techniques. Human movements include static and dynamic characteristics. Static characteristics are also referred to as spatiotemporal parameters, and



**Fig. 1** Simplified diagram for motor function assessments in rehabilitation. TUG: timed up and go, BBS: Berg balance scale, SPPB: short physical performance battery, 6MWT: 6-min walk test, IMU: inertia measurement unit, EMG: electromyography, EEG: electroencephalogram.

they include step length, step width, distance, and time [25]. Stroke patients have an asymmetric gait pattern with a large difference in step length [26] or swing time on both sides [27]. Moreover, dynamic characteristics are time series parameters [25], which commonly include kinematic and kinetic parameters. Kinematic parameters include joint trajectories, joint angles, joint velocities, joint accelerations, joint range of motion, and trajectory of centre of mass (COM). Pickle et al. [28] evaluated the balance ability of patients with Parkinson’s using angular momentum calculated by the angular acceleration and velocity of segments. The sway distance between the COM and centre of pressure (COP) and the sway speed of COP are also used to assess balance ability [29]. A previous study used the correlation coefficient of the left and right joint angle curves to evaluate the asymmetry of hemiplegic gait [26]. The maximum stretching speed of the elbow joint was found to be related to the modified Ashworth scale used to assess spasticity [30]. A systematic review showed that almost half of the current exoskeleton performance evaluation studies used kinematic parameters [31]. Kinematic parameters can be obtained using tools such as inertial measurement units, infrared motion capture systems and image processing systems (Figs. 2(a) and 2(b)).

Kinetic parameters include torque, force, power, ground reaction force (GRF), and heel-contact force. The GRF and heel-contact force can be used to identify the gait events of heel strike and toe-off in patients with hemiplegia and spinal cord injury [32,33]. The maximum joint resistance can be used to evaluate muscle tension in patients with spasms [30]. Kinetic parameters can be used to quantify weakness in patients. For example, Neckel et al. [34] compared active joint torques between patients with chronic stroke and a control group and found that patients who suffered from a stroke were significantly weaker in six of the eight measures tested. Another study by this team comparing gait patterns of subjects wearing Lokomat showed that the kinematic patterns of the chronic stroke and control groups were similar. However, the kinetic parameters were different, with the hip extension torque and knee flexion torque of the uninjured side being significantly greater in patients with stroke than in the control group [35]. This suggests that although Lokomat uses symmetrical kinematic features to guide walking, the torque pattern remains asymmetric. Thus, further investigating ways to appropriately combine kinematic and kinetic parameters is necessary to better represent patients’ needs. The GRF and heel contact force can be obtained through measurements using a



**Fig. 2** Partial objective evaluation for motor function assessment: (a) infrared motion capture (Motion Analysis, USA); (b) inertial measurement units (Noraxon, USA); (c) insole plantar pressure and measurement device (Novel, German); (d) force plate (AMTI, USA); and (e) electromyography sensor (Noraxon, USA).

three-dimensional force plate system or a plantar pressure system. The pressure sensor in the insole can be placed in the shoe to measure the vertical force. A series of kinetic parameters, such as joint torque, can be calculated using the inverse dynamics method (Figs. 2(c) and 2(d)).

### 2.3 Biological-signal-based method

Surface electromyography (EMG) records muscle activity (Fig. 2(e)). The biological signals of the brain can also be recorded using electroencephalography (EEG). Muscle activity can be used to evaluate the effort required by patients to complete motor tasks [36] as well as abnormal muscle coactivation patterns [37]. A previous study has shown that the contraction of antagonistic muscles in stroke patients is very strong during ankle flexion and extension and knee extension [34]. Shestakov [38] used EMG to evaluate astronauts' ability to maintain body balance in the presence of external disturbances. At present, EMG is being used to identify motor intentions of healthy people [39]. However, as mentioned, patients with disorders, such as strokes or spasms, may induce abnormal muscle contractions, which also produce EMG signals. Therefore, identifying a patient's motor intention through EMG signals directly has limitations. EMG varies greatly among individuals when evaluating human movements as the muscle activity of maximum voluntary contraction is used for standardised processing. In addition, EMG is also affected by fatigue. These problems may limit the use of EMG in rehabilitation robots.

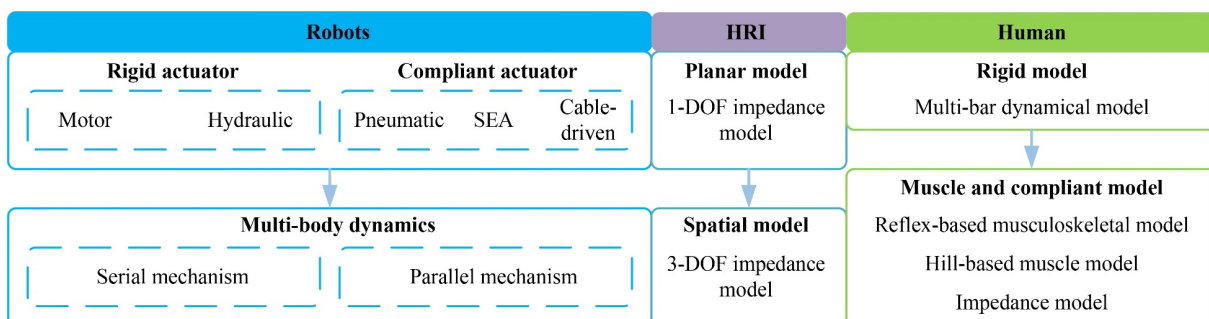
## 3 Modelling and perception of human–robot-coupled system

### 3.1 System modelling for three levels

Humans wear lower limb exoskeleton rehabilitation robots for rehabilitation training, forming a human–robot coupling system. Models of the coupling system can provide a basis for the design and control of the system. The modelling of such a system can be divided into three

levels based on its characteristics, including robot, human and human–robot interaction, as shown in Fig. 3.

The first level involves modelling the actuators. Lower limb rehabilitation robots often use electric motors and hydraulics. For the motor drive, the servo system is a three-closed-loop control including a position control loop, speed control loop and current control loop, which is generally simplified to a second-order differential link [40]. For hydraulic systems, the corresponding drive system model is usually set up according to the hydraulic components adopted, such as the general valve-controlled asymmetrical cylinder system [41]. Both these drives are rigid drives. To improve human–robot collaboration, studies have been conducted on the design of the drive system. On the one hand, pneumatic [42] drives with stronger flexibility are adopted, and on the other hand, serial elastic actuators (SEAs) [43] and cable-driven actuators [12] are adopted. At the level of the drive system, the elastic actuator is modelled. The drive is connected to the load via a compliant element. The drive dynamics are represented by the inertia and motor torque. According to the structure designed by SEA, the corresponding actuator modelling can be obtained by considering friction and other links [44]. The distribution of driven cables is various, potentially satisfying different requirements of the robot and obtaining better performance. More emphasis should be put on the unidirectional characteristics and the coupling relationship of cables [5]. In the process of driving modelling, the most important problem is the identification of system parameters and the accuracy of the model that affects the control effect. Another aspect is the modelling of the robot system level. Lower limb exoskeleton rehabilitation robots generally adopt serial structures after simplifying the joints of the human lower limbs [2]. In recent years, parallel structures have also been reported based on further studies of real human movement [8,45,46]. The series and parallel structures are rigid structures. The Lagrange method [47] and Newton–Euler method [48] can be used to establish dynamic models for rigid-body dynamics modelling, which is widely used in industrial robots. For the lower limb exoskeleton robot in a series



**Fig. 3** Modelling of robot, human, and human–robot interaction. HRI: human–robot interaction, DOF: degree of freedom, SEA: serial elastic actuator.

configuration, the robot is simplified into a multi-link model, and dynamic modelling of the lower limb exoskeleton robot is carried out [49]. For robots with parallel configurations, similar ideas as in industrial robots can be used for dynamic modelling [9].

In a lower limb exoskeleton rehabilitation robot, the process of modelling is insufficient to consider the robot itself, but it also needs to include the human body to realise the modelling of the human–robot coupling system. The human lower limb was simplified into a multi-link model based on the simplification of its each joint [50]. Existing multi-link models are mainly derived by simplifying the sagittal plane movement of the human body. Generally simplified to two- [51] and three-DOF link models [49], the five- [52] and seven-bar human dynamics models [53] without and with consideration of the ankle joint, respectively, are established. Different dynamic models have been established according to the difference between the support and swing phases [54]. The main function of establishing these models is to calculate the corresponding joint torques of the human body. However, due to the existence of the musculoskeletal system of the human body, a rigid body cannot be simply used to represent the dynamic model of the human body. Therefore, the muscle model is also used to conduct dynamic modelling of human lower limbs [55,56] and the human reflex-based musculoskeletal model [57,58] is used to obtain the driving torque. However, from the perspective of control, as the human body is equivalent to an impedance model including stiffness and dumping for processing, the dynamics modelling of lower limbs is not performed [59] to form a human–robot coupling system together with the robot model. All of the above models cannot accurately describe the rigid-flexible coupling characteristics of human lower limbs caused by the musculoskeletal system. The model is not accurate due to the large difference in inertia parameters of the human body which are difficult to accurately measure. Such a mapping relation is different from person to person, and individual differences are large, making application difficult. Concurrently, for patients who need to carry out passive movements, their ability for performing activities is weak, they cannot generate a torque that is calculated according to the musculoskeletal model and their EMG signals are difficult to collect.

The human body and the robot are not rigidly connected but are usually connected through flexible links such as straps [9] via which human–robot interaction (HRI) forces act. The existence of interaction forces realises force and energy transfer between the robot and the human body. For such an interaction force model, a K–B model with a single degree of freedom (DOF) was proposed [60]. To expand the model, a K model with three DOFs was proposed [9]. The main problems of these models are as follows: The parameters of the

impedance model are inaccurate. These models also assume that the joint centre of the human body and the joint centre of the robot coincide, but the influence caused by the joint centre mismatch is not considered. Furthermore, when using the multi-link model for human–robot coupling dynamic modelling, we tend to assume no deviation occurs in the movement between the human and robot, thus assuming a rigid connection between the human and robot. However, particularly in the early stage of the rehabilitation, for the patient, the interaction force owing to the motion deviation between the human and robot drives the human body to move. If no deviation occurs, no interaction force occurs, creating contradictions in the multi-link model.

### 3.2 Perception for rehabilitation

As a human-centred intelligent system [61], the lower limb exoskeleton rehabilitation robot needs to fully perceive the information of the human–robot coupling system through a sensing system and identify the motion state and intended motion of the patient to realise effective human–robot coordination, ensure a smooth and effective control strategy and achieve the effect of rehabilitation. Thus, a perception system is a key component of the system to realise human–robot coordination control. Two types of information are obtained by the perception system. One is the information from physical and biological sensors, which reflects the motion and state of the human–robot coupling system. The other is HRI information, which accurately predicts the intended movements of patients (Fig. 4).

For robot systems, perception can be achieved using physical sensors. Linear and rotary potentiometers and force sensors can be set at the joint to measure the output angle and torque of the joint [5]. The plantar pressure information can be detected using plantar pressure sensors and ground reaction force sensors [62]. The collection of this physical information and input into the control system can serve as a feedback link and provide a basis for the design of the controller.

A lower limb exoskeleton rehabilitation robot is a typical human–robot coupling intelligent system, which also needs to perceive the relevant information of the human body. However, biological signals are collected to identify the intended human movement. The sensor mode based on EMG serves as the input signal of the controller [63] to identify muscle strength or gait for corresponding control or the method of electromyographic fusion [64]. Through mechanism analysis of brain signals [65] and intention recognition [66], great progress has been made in the research on intention perception of exoskeletons based on EEG signals [67,68]. Bioelectric sensing information can directly reflect the movement intention of the wearer, due to its advantages of strong global stability, fast response and being the most natural HRI.

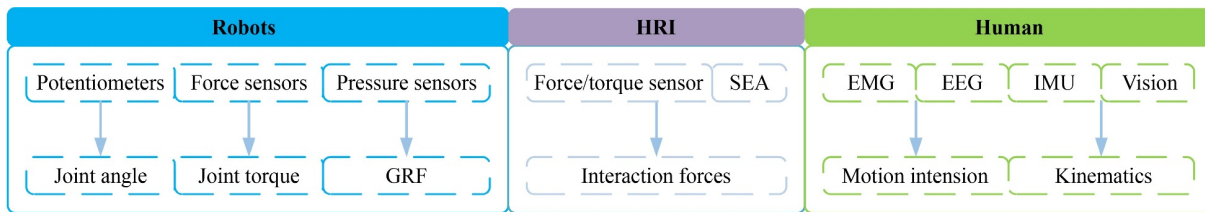


Fig. 4 Perception of robot, human, and human–robot interaction.

However, individual differences exist in bioelectrical signals, and the mapping mechanism between bioelectrical signals and human motion intention needs to be further studied. By contrast, physical sensors can be used to detect the movement information of the human body, and the IMU can be used to detect the movement information of the body for the identification of the movement intention [69] and gait phase estimation [70]. The IMU can also be used to detect the joint angles of the lower limbs [55,71]. For such an attitude detection algorithm, a precision problem arises [72,73]. A vision sensor can also be used to detect the posture of the human body [11].

Detection of HRI forces is also an important method to realise human–robot coordinated control. Such forces are mainly measured in the following ways: The force/torque sensor is installed between the robot and the binding joint is used to detect the interaction forces [74,75]. The direction and magnitude of the multiple interaction forces were used to comprehensively determine the motion intention. Force information is collected using two-dimensional interaction force sensors installed between the robot and the cuff, and the interaction torque is determined using the product relationship and the installation position. A uniform sensor is used to measure the interaction force information and identify the motion intention of the human body [76]. Series elastic actuators [44] are used to detect and identify interaction forces to realise human–robot coordinated control. This approach increases the complexity of the structure. The measurement of interaction forces is also affected by the number and arrangement of the sensors.

#### 4 Human–robot coordinate control strategies

The recovery cycle is divided into three stages. Phase I is considered an inpatient program, with an average duration of 7 to 10 days with the objective to maintain the patient’s muscular tone by performing passive movements, low-intensity exercise and education to reduce risks. Phase II is a twice-weekly outpatient program, with an average duration of three months that consists of a combination of physical exercise on a treadmill, an education program oriented to the prevention of risk factors and adoption of healthy habits (e.g., controlling

blood pressure, cholesterol, weight and stress management). Finally, Phase III is defined as a long-term maintenance period, with the objective to provide reinforcement to the already-acquired routines in previous phases and to provide advice concerning secondary prevention [77]. Therefore, for the initial stages of I and II, the robot can be used to fully drive the affected limb to move to achieve passive rehabilitation training. In the middle and late stages of II, the patient’s motor ability is recovered, so the robot cannot be simply controlled passively. Evaluating the patient’s motor ability and state and adopting different rehabilitation training methods are necessary to realise active rehabilitation training. In Phase III, after a period of training, the patient recovers their motor ability. At this time, the robot is needed to assist the patient in daily life to perform routine exercises. At present, lower limb rehabilitation robots pay more attention to Phases I and II, whereas Phase III is classified as assistance. Starting from the entire cycle of I–III, this study considers that part of III also belongs to lower limb rehabilitation robots. Rehabilitation goals may vary at different stages of a disease. A physical activity and exercise plan must be formulated according to the patient’s tolerance, recovery stage, environment, social support, physical activity preference, and activity, and participation restrictions. According to the American Heart Association and Stroke Association, bed rest needs to be minimised and a patient must sit or stand intermittently to maintain endurance during acute recovery. When the patient is stable, physical and occupational therapy are used to promote motor recovery, such as gait, muscle strength or balance. The goal of the third phase of stroke rehabilitation is to promote the completion of recommended physical activities and exercise to prevent cardiac problems and recurrent strokes [78].

According to the patient’s condition and different rehabilitation training stages, different rehabilitation training modes need to be adopted, and corresponding control methods should also be used (Table 1 [5,51,57,62,79–85]). Robot-assisted rehabilitation training can be divided into passive and active training. Generally, lower limb rehabilitation robots adopt the method of active and passive mixed control [86,87]. In early stages of rehabilitation training, due to the reduced strength of patients’ limbs, passive control is needed; that is, robots drive the patient’s limbs to carry out continuous passive training to achieve continuous passive movement. The

**Table 1** Overview of control methods

Control strategies	Methods	Features
Passive control	Proportional–derivative (PD) control [79], computational torque control [62], variable structure control [80], impedance control [81], multiple input multiple output (MIMO) decoupling control [51]	After a walk mode based on the sensors was selected, the participant initiated and propagated the programmed motions. The torque that the robot needs to apply to the human body is generally put into the dynamics equation as a disturbance term
Assist-as-needed control	Force-field control (FFC) [5], moment-field control (MFC) [82], three-dimensional-force-field control (3D-FFC) [83]  Neuromuscular control [57]	Using physical sensors for measurement and evaluation; that is, the actual position or attitude deviation measured by the sensor can obtain the corresponding adjustment force/torque to achieve impedance control based on the attitude deviation  Capturing EMG signals to generate a synchronised and natural gait and achieve human–robot coordinated control
Force control	Finite state machine [84]  EMG-based control [85]	A finite state machine is used to indicate the intended option of a series of manoeuvres. The intended manoeuvre of the user based on the provided inputs is determined. Each state is defined by a set of joint angle trajectories, which are enforced by position control loops  Human joint torque is estimated based on EMG signals to generate virtual torque for the control of the motors

passive control mode is aimed at patients with severe diseases and weak muscle strength; here, the affected limbs are driven by the robot to move along a predetermined trajectory. From the perspective of robot control, robots perform trajectory tracking tasks in passive training, which can be achieved through trajectory tracking control methods, such as proportional–derivative (PD) control [79], computational torque control [62], variable structure control [80] and impedance control [81]. The controller mentioned above does not take humans into account; that is, the trajectory tracking control realised focuses on the movement of the robot and the tracking of expected motion. In the design of the controller, the torque that the robot needs to apply to the human body is generally put into the dynamics equation as a disturbance term [88,89]. Then, the dynamic control of the robot is carried out. A structured or unstructured reach exists in the robot system, and the uncertainty of the non-structure, multiple input multiple output (MIMO) decoupling control method is used for compensation control [51].

For patients who can actively exert force in the middle and later stages of rehabilitation, the robot will provide the necessary assistance according to the patient’s motion intention. Owing to the high degree of active participation of patients in active training and good stimulation of the nervous system, the clinical rehabilitation effect at this stage is better than that of passive training [90]. In active training, the robot needs to provide corresponding assistance according to the motion intention and state of the patient [91]. By using a method based on impedance control, an environment with different impedance characteristics is simulated to ensure compliance with the interaction process; thus, an assisted procedure is proposed [92]. As on-demand auxiliary control, an important problem is how to assess the patient’s motion intention and state and then give the corresponding auxiliary force. One way is to use physical sensors for measurement and evaluation; that is, the actual position or attitude deviation measured by the sensor can obtain the

corresponding adjustment force/torque through the corresponding force-field control (FFC) [5], moment-field control (MFC) [82] and three-dimensional-force-field control (3D-FFC) [83] to achieve impedance control based on the attitude deviation. To increase the flexibility of the system, the term to the adaptive control law is reduced by adding a novel force, decaying the force output from the robot when errors in task execution are small [93]. This type of controller has two drawbacks that limit its application. First, the motion intentions and status of the patients are evaluated based on the position and attitude information of the robots. However, as discussed, deviation occurs in the motion between the patients and the robots, implying that the feedback information in the controllers cannot accurately reflect the motion of the patients. Second, the parameters in the controllers are fixed but cannot be changed according to different patients, indicating that the controllers have inadequate adaptability. Another approach is to capture EMG signals, and neuromuscular control reacts to the movements of the thighs, resulting in a synchronised and natural gait [57]. The motion intention of the human body is detected through the neuromuscular model to achieve human–robot coordinated control.

When rehabilitation training reaches a certain stage, the lower limb exoskeletons can provide assistance to the patients for their daily life. At this stage, lower limb exoskeletons tend to be over ground. In this case, the preprogrammed method can still be used to drive the human body to move [94], but this control mode is difficult to adapt to complex and changing situations of the actual walking process. In this process, more attention is paid to HRI and human–robot coordinated control. On the one hand, the interactive force is used to identify the motion intention of the human body to achieve assistance of the lower limbs in the walking process [54,95]. On the other hand, it is different from the rehabilitation training stage [96]. At this time, the trajectory is no longer pre-set, but can be obtained by real-time reference changes [97,98]. A finite-state machine defines different motion

scenarios and logic to provide the desired assistance for patients [84]. However, biological signals can be used to identify the motion intention of the human body to assist in the walking process, and the EMG model can be used to calculate the driving torque in real time [55] or the mapping relationship between the EMG signal and joint torque [85] can be used to realise human–robot coordinated control.

The robot system can detect robot motion information, human motion information and HRI information for human motion perception and state evaluation. The information of joint angle, torque and plantar pressure can only reflect the motion state of the robot. Individual differences exist in surface EMG, EEG and other biological signals, and the mapping mechanism between them and human motor intention is insufficient. Interactive force information can be detected by force/moment sensors and distributed sensors between the human and robot; however, this increases the complexity of the structure, and the measurement results are affected by the number of sensors and layout. Biological signal information and interaction force information are mainly used to perceive the intention of human movement and are generally used as a trigger quantity in the process of use. Therefore, achieving accurate perception of human movement is difficult. Physical sensors are used for measurement and evaluation, that is, the actual position or attitude deviation measured by sensors can be adjusted by force/torque controllers such as force field, screw field and torque field controllers to achieve impedance control based on position and attitude deviation. These methods are position deviations of the robot for evaluation basis. However, the flexible connection between human movement deviation and the resulting position deviation may not accurately reflect the state of patients with intention, and the controller parameters are usually fixed and cannot adapt to the needs of different patients with different stages of illness, leading to insufficient human–robot coordination. The control method of biological signals such as EMG and EEG, although directly measuring human signals, is insufficiently accurate, also leading to the lack of human–robot coordination.

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## 5 Discussion

Recovery from disease is a complex process, possibly done through a combination of spontaneous and dependent learning [99]. Task-specific and context-specific training are widely accepted principles in motor learning, indicating that rehabilitation training should be targeted at goals related to patients' needs [100]. The results of a systematic review showed that at present, almost half of the studies on the evaluation of lower limb exoskeleton performance are focused on flat ground or treadmill, indicating that the exoskeleton field mainly focuses on

basic motor skills, while other motor tasks, such as standing, balance, walking on irregular terrain, turning and lateral movement, have been largely ignored [31]. The simultaneous solution of several other important functional tasks may also be a problem for rehabilitation robots.

### 5.1 Demand for robotic rehabilitation

Dysfunction is a major disease-related problem. Rehabilitation should focus mainly on improving activity and functional limitations; thus, exercise and functional recovery play an important role in modern rehabilitation [101]. Different diseases may lead to different dysfunctions. Decreased muscle strength is the most significant injury after stroke, further reducing walking speed and endurance [102]. Incomplete spinal cord injury (SCI) can cause motor dysfunction below the injury level, and walking is one of the most desired goals for many patients with SCI [103]. Dysfunction with different causes may share the same mechanism and consequences, leading to the same clinical syndrome, and responding to the same interventions [104]. For example, walking disorders may be caused by decreased muscle strength or balance, which may result from stroke, SCI or other diseases. Therefore, the focus must be on dysfunction and not only the disease causing the disorder in the rehabilitation process. At present, rehabilitation robots mainly focus on training different types of patients to walk, mainly because walking is one of the main goals of patients with motor dysfunctions. Walking is also one of the main methods via which patients can perform and participate in other activities. Fewer rehabilitation robots focus on other functional disorders, such as balance, muscle weakness, and body transfer.

Therefore, to adapt to different conditions and functional disorders, lower limb exoskeleton rehabilitation robots need to have personalised characteristics and be able to fulfil new requirements for human–robot coordination and control. Many studies on human–robot coordination in different stages of robot-assisted rehabilitation training have been published, but research on different conditions is insufficient. The pathological characteristics of different diseases are not the same. Even if the rehabilitation robot is also used for rehabilitation training, the way of rehabilitation training is not the same. Therefore, developing a program suitable for robot-assisted rehabilitation training for different conditions is necessary to show different human–robot coordination problems. At present, some studies combine a certain index that can be measured by robots with dysfunction, and human–robot coordination methods can be designed by sensing these kinematic or dynamic indicators of patients. However, no comprehensive evaluation model has been developed for a disease or dysfunction, which is also urgently needed in the future.



## 5.2 Modelling for human–robot coupling system with new structures

To adapt to different tasks, environments and rehabilitation needs, prototypes need to be lightweight and miniaturised. The presently used drive and transmission mechanisms occupy a large proportion of overall prototypes, resulting in a heavy system. At the same time, the flat joint, small volume and high energy density have important significance for realising the strong quantification and comfort design of the lower limb exoskeleton rehabilitation robot. To obtain a high power/thrust density [105], an innovative design of the drive system is available; its corresponding exokinematic modelling is required to achieve accurate control, thereby placing new requirements on the construction of the drive model. In addition, the idea of modularisation is to select corresponding modules according to different stages of illness to achieve structural restructuring [43,45]. Lightweight and miniaturised drive and transmission mechanisms can also make modular design easier to achieve. The human-in-the-loop design is an important method for modular design, based on the human–robot coupling dynamical model. The lower limbs were simplified into a multi-link model, and the rigid body dynamics modelling method was used to model the human–robot coupling system. However, accurately describing the rigid–flexible coupling characteristics of human lower limbs caused by the musculoskeletal system, and the inertia parameters of the human body vary greatly, making it difficult to accurately measure, resulting in uncertainty. Human–robot energy transfer is realised by the interaction force generated by flexible links, such as binding. The interaction force modelling method based on the spring damping model has model parameter uncertainty, and the model does not consider the effect of human–robot joint centre not coinciding, thereby influencing the accuracy of the model. Therefore, a research hotspot in realising the control mode of human in the loop is the establishment of a rigid–flexible coupling model in line with the characteristics of the human musculoskeletal system and a human–robot coupling dynamics model in conjunction with the robot dynamics model. The rigid–soft coupling structure is closer to the actual musculoskeletal structure of the human body [106]. How to carry out structural modelling in this aspect and realise the modelling of a human–robot coupling dynamics system is also an important problem.

## 5.3 Assessment methods with different etiologies based on multi-mode sensors

Traditional assessment methods can be used to comprehensively assess human locomotion ability, but these methods are mostly qualitative or post-qualitative and cannot meet the real-time assessment needs of lower

limb exoskeleton rehabilitation robots. A perception system, used for real-time perception and evaluation of human motor functions, and the adaptive adjustment of the corresponding rehabilitation training, are also required. Contemporary research on flexible sensors and electronic skin [107] will facilitate the design of perception systems. First, designing comprehensive models based on the mapping relationship between motor functions and multi-sensor information is necessary, and the redundancy of information should be considered to simplify the systems. Perception systems should also be designed to dynamically sense humans' motion, accurately understand their intentions and evaluate their motor functions in real time. Compared with single-sensor data, processing multi-modal information through multi-source fusion can ensure the speed and accuracy of perception. Such processing can combine the advantages and disadvantages of the various sensors mentioned in this paper to construct the perception mode of bio-machine mixed signal and design data fusion algorithm, which is also a research hotspot. For example, IMU and EMG were used for hybrid detection, and a neural network was used to perceive and predict the motion of the knee joint [108]. By making full use of the learning algorithm, the multi-mode multi-sensor information analysis and processing and data fusion algorithm are constructed. Thus, the perception system can sense more complete information and higher-level features of the robot and human body according to the multi-mode information acquired and realise adaptive sensing. At the same time, through the in-depth combination of machine learning [109] and other technologies, the customisation and parameterisation of data diagnosis and treatment are realised, and the integration of autonomous learning and people is better realised [77]. The combination of virtual reality and augmented reality technology [110] enables a real scene to stimulate the brain and significantly stimulate motor function [111]. Using visual interaction and virtual reality technology is necessary [112]. At the same time, the current perception system is more used to sense the motion intention of the human body and then adjust the output force/moment of the robot accordingly to achieve human–robot coordinated motion. However, the comprehensive evaluation of the human motion ability is not considered in the perception system, which are basis for the diagnosis and evaluation to realise human–robot coordination between the movement according to different conditions and phases.

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## 6 Conclusions

Human–robot coordination, which is crucial to lower limb exoskeleton rehabilitation robots used as human–robot coupling systems, is reviewed in this paper. First, patients' functional disorders and clinical rehabilitation

needs regarding lower limbs are analysed, forming the basis for the human–robot coordination of lower limb rehabilitation robots. Then, human–robot coordination is discussed in three aspects: modelling, perception, and control. The modelling of such a human–robot coupling system is described at three levels: robots, humans, and HRI. Two types of information, namely, information from physical and biological sensors and HRI information, are discussed, and the design method for the perception system is analysed. Control strategies for different stages throughout the recovery cycle are illustrated and analysed. The demand for robotic rehabilitation, modelling for human–robot coupling systems with new structures and assessment methods with different etiologies based on multi-mode sensors are discussed in detail, suggesting development directions of human–robot coordination and providing a reference for relevant research.

## Nomenclature

COM	Centre of mass
COP	Centre of pressure
DOF	Degree of freedom
EEG	Electroencephalography
EMG	Electromyography
FFC	Force-field control
GRF	Ground reaction force
HRI	Human–robot interaction
IMU	Inertial measurement unit
MFC	Moment-field control
MIMO	Multiple input multiple output
PD	Proportional–derivative
SCI	Spinal cord injury
SEA	Serial elastic actuator
TUG	Timed up and go

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